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Joint Source-Channel Coding for Semantics-Aware Grant-Free Radio Access in IoT Fog Networks

Johannes Dommel, Zoran Utkovski, Osvaldo Simeone and Sławomir Stańczak

Abstract—A fog-radio access network (F-RAN) architecture is studied for an Internet-of-Things (IoT) system in which wireless sensors monitor a number of multi-valued events and transmit in the uplink using grant-free random access to multiple edge nodes (ENs). Each EN is connected to a central processor (CP) via a finite-capacity fronthaul link. In contrast to conventional information-agnostic protocols based on separate source-channel (SSC) coding, where each device uses a separate codebook, this paper considers an information-centric approach based on joint source-channel (JSC) coding via a non-orthogonal generalization of type-based multiple access (TBMA). By leveraging the semantics of the observed signals, all sensors measuring the same event share the same codebook (with non-orthogonal codewords), and all such sensors making the same local estimate of the event transmit the same codeword. The F-RAN architecture directly detects the events' values without first performing individual decoding for each device. Cloud and edge detection schemes based on Bayesian message passing are designed and trade-offs between cloud and edge processing are assessed.

Index Terms—approximate message passing, fog-radio access network, random access, type-based multiple access, semantic communications.

I. INTRODUCTION

DUE to the growing interest in Internet-of-Things (IoT) applications, there has been an intense research effort on massive machine-type communications (mMTC) for 5G networks and beyond [1]–[3]. In these networks, standard medium access control protocols that recover the individual messages of participating devices require spectral resources that scale at least linearly with the number of active users [4]–[7]. This paper proposes the integration of two distinct mechanisms that aim at reducing the communication overhead, namely (i) the use of cloud and edge processing in fog-radio access networks (F-RANs) [8]; and (ii) the application of semantics-aware medium access protocols that are designed to recover the aggregated information of interest rather than the individual messages (see, e.g., [9], [10]). To elaborate, we consider a multi-cell F-RAN architecture [8], as illustrated in Fig. 1, where IoT devices are connected to edge nodes (ENs) in a cell-free fashion. Each EN is connected via a finite-capacity fronthaul link to a central processor (CP). In the system under study, multiple IoT sensor devices measure correlated events and transmit messages in a grant-free fashion via wireless channels to the ENs. The events may be inactive,

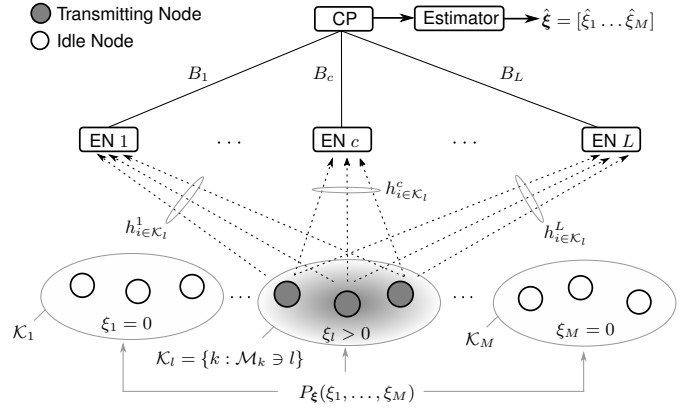


Fig. 1. A wireless fog-radio access network (F-RAN) for event driven random access: a set of sensors \mathcal{K} monitors jointly M independent events, with each event m being either inactive ($\xi_m = 0$) or active with an associated scalar state value $\xi_m \in \{1, \dots, R\}$. Each sensor $k \in \mathcal{K}_m \subset \mathcal{K}$ measuring an active event $m \in \mathcal{M}_k$ transmits a message to L edge nodes (ENs) over a wireless fading channel. The ENs are connected via capacity-limited fronthaul links of capacity B_1, \dots, B_L to a central processor (CP) for joint decoding and estimation of the events values $\hat{\xi} = [\hat{\xi}_1 \dots \hat{\xi}_M]$.

and functions of multiple IoT sensors' measurements, rather than individual measurements, are of interest to the receiver. In information-theoretic terms, the problem is thus not one of channel coding in a multiple-access channel (MAC) for reliable communication of individual messages, but rather that of joint source-channel (JSC) coding for effective inference of correlated quantities of interest (QoIs).

Related work: A notable instance of information-centric MAC protocols is type-based multiple access (TBMA) [11]. With TBMA, each measurement value for a given QoI is assigned an orthogonal codeword, and the receiver infers the desired QoI from a histogram at the outputs of a filter-bank matched to the codewords [11]–[13]. A potentially more efficient solution based on a non-orthogonal generalization of TBMA has been proposed in [14]. Accordingly, all sensors measuring the same event share the same codebook with non-orthogonal codewords, and the base station directly detects the events' values using a Bayesian message passing technique. Recently, TBMA has been extended to multi-cell F-RANs for IoT applications under centralized or decentralized decoding in [15].

Contribution: In this paper, we study the integration of cloud detection in F-RAN with grant-free transmission based on the semantics-aware non-orthogonal TBMA protocol [14]. In the proposed approach, detection is performed in a centralized fashion in the cloud based on either detect-and-forward (DtF) [16] or quantize-and-forward (QF) utilizing capacity

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limited fronthaul links. We design DtF and QF schemes based on Bayesian message passing by leveraging the hybrid generalized approximate message passing (H-GAMP) algorithm [17]. Finally, we numerically evaluate the relative performance of the proposed DtF and QF schemes under capacity-constrained fronthaul.

II. EVENT-BASED RANDOM ACCESS FOR FOG-IOT: SYSTEM MODEL AND CODING SCHEME

Scenario: We consider an F-RAN IoT architecture consisting of a set \mathcal{L} of L ENs, each connected to a CP unit via a capacity constrained fronthaul link, as illustrated in Fig. 1. In this scenario, a set \mathcal{K} of K devices jointly monitor a set \mathcal{M} of M multi-valued events. Each event m is characterized by an independent scalar random variable $\xi_m \in \{0, 1, \dots, R\}$, with $P_\xi(\xi_m = 0) = 1 - \rho$ for some $0 \leq \rho \leq 1$ representing the probability that event m is inactive. When the event is active, the event variable ξ_m takes one of the values in the set $\{1, \dots, R\}$, so that parameter R (or, more properly, its logarithm) measures the amount of information attached to the occurrence of an event. Each device k can simultaneously monitor a subset of events $\mathcal{M}_k \subseteq \{1, \dots, M\}$. Therefore, the devices can be partitioned into M , generally overlapping, groups $\mathcal{K}_m = \{k \in \{1, \dots, K\} : \mathcal{M}_k \ni m\}$.

Coding scheme: Each device k performs a local (real-valued) measurement u_k , which is, in general, correlated with all the variables ξ_m for $m \in \mathcal{M}_k$. For each event $m \in \mathcal{M}_k$, the local measurement u_k is mapped to a value $\phi_m(u_k) \in \{0, 1, \dots, R\}$, which is the *local estimate* of event m . For transmission, each local estimate $\phi_m(u_k)$ is mapped by device k into a codeword $\mathbf{s}_{\phi_m(u_k)}^m \in \mathbb{C}^{N \times 1}$, subject to a power constraint $\|\mathbf{s}_{\phi_m(u_k)}^m\|_2^2 \leq 1$. The codewords for each event m are selected from a shared codebook $\mathbf{S}^m = [\mathbf{s}_0^m \dots \mathbf{s}_R^m] \in \mathbb{C}^{N \times (R+1)}$ of $R+1$ generally non-orthogonal codewords (columns). For future reference, we define $\mathbf{S} = [\mathbf{S}^1 \dots \mathbf{S}^M] \in \mathbb{C}^{N \times M(R+1)}$ to be a matrix that collects all codebooks.

Channel model: We assume time synchronization and transmission over a block-fading channel model with coherence time–frequency span no smaller than that occupied by the codewords’ duration. The signal received at EN c can be written as

$$\mathbf{y}^c = \sum_{k \in \mathcal{K}} h_k^c \sum_{m \in \mathcal{M}_k} \mathbf{s}_{\phi_m(u_k)}^m + \mathbf{v}^c, \quad (1)$$

where h_k^c denote the fading coefficient for the link between device k and EN c , which is assumed to be identical and independent distributed (i.i.d.) $\sim \mathcal{CN}(0, \sigma_h^2)$, and $\mathbf{v}^c \in \mathbb{C}^{N \times 1}$ the additive noise vector with elements i.i.d. $\sim \mathcal{CN}(0, \sigma_v^2)$.

To obtain a matrix notation, we define for each device k the binary *measurement* vector

$$\mathbf{c}_k = [(\mathbf{c}_k^1)^T \dots (\mathbf{c}_k^M)^T]^T \in \{0, 1\}^{M(R+1) \times 1}, \quad (2)$$

with

$$\mathbf{c}_k^m = \begin{cases} \mathbf{e}_{\phi_m(u_k)} & \text{if } m \in \mathcal{M}_k \\ \mathbf{e}_0 & \text{otherwise,} \end{cases} \quad (3)$$

where \mathbf{e}_r is an $R+1$ -dimensional binary vector with a single non-zero-entry at the $(r+1)$ -th position.¹

With this definition, the received signal (1) at EN c can be described in matrix-notation as $\mathbf{S}\mathbf{x}^c + \mathbf{v}^c$ with

$$\mathbf{x}^c = (\mathbf{h}^c \otimes \mathbf{I}_{M(R+1)})^T \mathbf{c}, \quad (4)$$

where $\mathbf{h}^c = [h_1^c \dots h_K^c]^T$ is the vector of channel coefficients; \otimes the Kronecker product; $\mathbf{I}_{M(R+1)}$ the identity matrix of size $M(R+1)$ and $\mathbf{c} = [\mathbf{c}_1^T \dots \mathbf{c}_K^T]^T$ the stacked vector of measurements. Note, that \mathbf{x}^c is a (sparse) Bernoulli-Gaussian vector, where each non-zero element constitutes the superposition of complex-normal fading coefficients.

Fronthaul constraint: We assume a packetized fronthaul transmission, e.g., via Ethernet, by considering a limited overall number of bits B_c that each EN c can communicate error-free to the CP per *fronthaul use*.

Error probability: The CP aims at estimating the state of each event $\hat{\xi} = [\hat{\xi}_1 \dots \hat{\xi}_M]$, where the average (per event) error probability is defined as

$$P_e \doteq \frac{1}{M} \sum_{m \in \mathcal{M}} \Pr\{\xi_m \neq \hat{\xi}_m\}. \quad (5)$$

We note that the outlined MAC protocol can be considered as a generalization of TBMA [11], given that the latter assumes a single event, i.e. $M \doteq 1$, and the use of $R+1$ *orthogonal* codewords of length $N \geq R+1$.

III. F-RAN PROCESSING WITH LIMITED FRONTHAUL CAPACITY

In this section, we introduce a Bayesian decoder based on generalized approximate message passing (GAMP). The proposed approach extends the decoder introduced in [14] from single EN-detection to the F-RAN architecture discussed in Section II. We derive a graphical model and develop two fronthaul processing schemes: (i) DtF, whereby each EN produces local estimates and forwards quantized soft-information to the CP; and (ii) QF, whereby each EN directly forwards a quantized version of the received signal to the CP.

Graphical Model: The relation between the involved *random* variables, i.e. the (input) $\mathbf{x} = [(\mathbf{x}^1)^T \dots (\mathbf{x}^L)^T]^T$, the (output) observations $\mathbf{y} = [(\mathbf{y}^1)^T \dots (\mathbf{y}^L)^T]^T$ and the (hidden) variables ξ can be described at the CP via a graphical model, where the input \mathbf{x} depends on $\xi \sim P_\xi$ via the mapping (2)-(3), which we denote as $p_{\mathbf{x}|\xi}$. The output \mathbf{y} is generated subject to the conditional probability distribution function (pdf) $p_{\mathbf{y}|\mathbf{z}}$ capturing the effect of the additive white Gaussian noise, where $\mathbf{z} = [(\mathbf{z}^1)^T \dots (\mathbf{z}^L)^T]^T$ is the output of a (dense) linear mixing $\mathbf{A}\mathbf{x}$ with $\mathbf{A} = \mathbf{I}_L \otimes \mathbf{S}$. According to our transmission scheme, the i -th element of \mathbf{z}^c is defined as $z_i^c = (\mathbf{a}_i^c)^T \mathbf{x}^c$ with \mathbf{a}_i^c being the i -th row of $\mathbf{A}^c = \mathbf{S}$, which is the c -th block of \mathbf{A} . In the following, we adopt the graphical model for QF and DtF considering a limited fronthaul capacity.

¹ \mathbf{c}_k can be interpreted as a *one-hot* encoding of all estimates at device k .

A. Quantize-and-Forward

With QF, each EN $c \in \mathcal{L}$ forwards a quantized version of the received symbols $\hat{\mathbf{y}}^c = \mathcal{Q}^c(\mathbf{y}^c)$ via the fronthaul link, and the CP uses $\tilde{\mathbf{y}} = [(\hat{\mathbf{y}}^1)^T \dots (\hat{\mathbf{y}}^L)^T]^T$ to carry out joint decoding. The impact of the fronthaul quantization can be modeled as Gaussian test channel [18], such that (1) received via the c -th fronthaul link from EN c at the CP can be written as $\hat{\mathbf{y}}^c = \mathbf{y}^c + \mathbf{q}^c$ where $\mathbf{q}^c \in \mathbb{C}^{N \times 1}$ represents the quantization noise vector with elements being i.i.d. $\mathcal{CN}(0, \sigma_{q^c}^2)$ [19]. Following rate-distortion arguments [20], $\sigma_{q^c}^2$ is upper bounded as $\frac{P}{2^{C_c} - 1}$, with P being the signal power and $C_c = B_c/N$ the fronthaul rate in *bit per complex sample*.

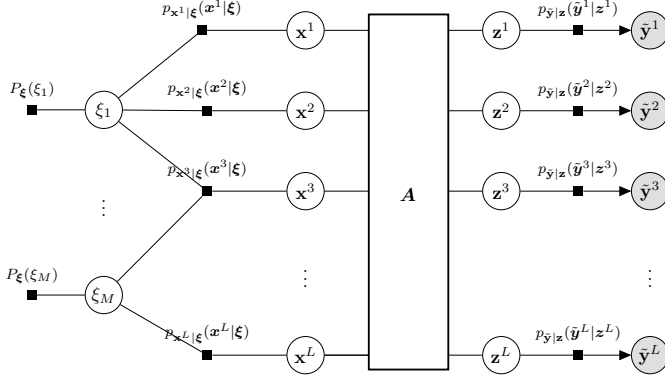


Fig. 2. Factor graph representation of the fog-radio access network (F-RAN) system under study with quantize-and-forward (QF).

By the factor graph representation, see Fig. 2, the joint pdf $p_{\xi, \mathbf{x}, \tilde{\mathbf{y}}}$ of the triple $(\xi, \mathbf{x}, \tilde{\mathbf{y}})$ factorizes as

$$\prod_{m=1}^M P_{\xi}(\xi_m) \prod_{j=1}^{LM(R+1)} p_{\mathbf{x}|\xi}(x_j|\xi_m) \prod_{i=1}^{LN} p_{\tilde{\mathbf{y}}|\mathbf{z}}(\tilde{y}_i|z_i), \quad (6)$$

where the conditional pdf $p_{\tilde{\mathbf{y}}|\mathbf{z}}$ captures the effect of the receiver- and quantization noise.

Given the factorization (6), the detector at the CP aims at computing the posterior distribution $p_{\xi|\tilde{\mathbf{y}}}(\xi|\tilde{\mathbf{y}})$ of the events' state vector ξ given the quantized observation vector $\tilde{\mathbf{y}}$. With QF, the relation between the structured sparsity introduced by the hidden variables ξ on the input variables \mathbf{x} , can be exploited using the H-GAMP algorithm [17], which provides an efficient solution with desirable empirical performance for group sparsity problems with overlapping groups. H-GAMP operates by iteratively exchanging soft information between two modules: the first carries out standard GAMP by treating the entries of the vector \mathbf{x} as independent, while the second refines the output of the first by leveraging the correlation structure of the entries of vector \mathbf{x} . With the posterior distribution, the CP calculates for each event the log-likelihood ratios (LLRs)

$$l_{m,r} = \ln \left(\frac{p_{\xi|\tilde{\mathbf{y}}}(\xi_m = r|\tilde{\mathbf{y}})}{p_{\xi|\tilde{\mathbf{y}}}(\xi_m = 0|\tilde{\mathbf{y}})} \right), \quad (7)$$

associated with the belief that event m is *active* with value $r \in [R]$. The estimator then selects the decisions for $\hat{\xi}_m$ as

$$\hat{\xi}_m = \begin{cases} 0 & \text{if } l_{m,r} < l_{m,r}^{th}, \quad \forall r \in [R] \\ \arg \max_{r \in [R]} l_{m,r} & \text{otherwise.} \end{cases} \quad (8)$$

The thresholds $l_{m,r}^{th}$ can be selected, e.g., to minimize the Bayesian risk [21] that included individual costs for false-alarm (false positive) and missed-detection (false negative).

B. Detect-and-Forward

With DtF, each EN $c \in \mathcal{L}$ performs *local detection* and forwards quantized soft-information to the CP. The CP then fuses the local decisions to obtain the final estimates for each event. For detection at each EN c , the joint pdf $p_{\xi, \mathbf{x}^c, \mathbf{y}^c}(\cdot, \cdot, \cdot)$ of the triple $(\xi, \mathbf{x}^c, \mathbf{y}^c)$ factorizes as

$$\prod_{m=1}^M P_{\xi}(\xi_m) \prod_{j=1}^{M(R+1)} p_{\mathbf{x}^c|\xi}(x_j^c|\xi_m) \prod_{i=1}^N p_{\mathbf{y}^c|\mathbf{z}}(y_i^c|z_i^c). \quad (9)$$

Using (9), the local detector at EN c aims at computing the posterior distribution $p_{\xi|\mathbf{y}^c}(\xi|\mathbf{y}^c)$ of the events' state vector ξ given the local observation \mathbf{y}^c . This can be done by applying the standard GAMP operating on $A^c = \mathbf{S}$.

Given the posterior distribution, each EN $c \in \mathcal{L}$ computes the local LLRs for all $r \in [R]$ and $m \in \mathcal{M}$ as

$$l_{m,r}^c = \ln \left(\frac{p_{\xi|\mathbf{y}^c}(\xi_m = r|\mathbf{y}^c)}{p_{\xi|\mathbf{y}^c}(\xi_m = 0|\mathbf{y}^c)} \right), \quad (10)$$

associated with the (local) belief at EN c , that the event variable ξ_m is active with value r . For transmission over the capacity-constraint fronthaul, each EN c applies a quantization function $\tilde{x} = \mathcal{U}^c(x)$, to the LLRs (10) according to the fronthaul bit-budget of B_c/M *bit per event* for all $m \in \mathcal{M}$. At the CP, the beliefs are reconstructed and merged to obtain

$$\tilde{l}_{m,r} = \sum_{c \in \mathcal{L}} \tilde{l}_{m,r}^c, \quad r \in [R], \quad (11)$$

which is associated with the (global) belief that the event variable ξ_m is active with value $r \in [R]$. Finally, the CP estimates the event activity variable by comparing (11) against thresholds, c.f. (8). We note that in the case of DtF, an optimal compression performance can be achieved by using an entropy quantizer operating on the MR -dimensional vector of LLRs.

IV. NUMERICAL RESULTS

We assume a dense network with $K = 80$ devices observing in total $M = 8$ events with $R = 4$ values in an F-RAN deployment with $L = 4$ ENs and fronthaul bit budget $B_c = B$, for all fronthaul links between the ENs $c \in \mathcal{L}$ and the CP. Each event has an activation probability $\rho = 0.1$ and the devices are configured such that each individual device observes only one of the events and that the total number of devices is partitioned into M non-overlapping sets $\{\mathcal{K}_m\}$, each of cardinality 10. The variance of the channel coefficients, which we recall are unknown to the transmitter devices and the receiver, is set to $\sigma_h^2 = 1$. To increase the energy efficiency,

each device k is configured for transmission, *only* if the locally observed event $m \in \mathcal{M}_k$ is *active*, i.e., if $\phi_m(u_k) > 0$. The signatures of the shared codebook \mathcal{S} of length N are generated randomly with entries being i.i.d. $\sim \mathcal{CN}(0, 1/N)$. We note that the convergence of approximate message passing (AMP) for this codebook has been studied rigorously in the asymptotic limit [17]. The average signal-to-noise ratio (SNR) is defined *per user* as $\text{SNR} \triangleq 1/\sigma_v^2$. For DtF, only the LLRs associated with the non-zero entries of the estimated event activity pattern are quantized and forwarded to the CP. The threshold for DtF and QF is chosen to minimize the error probability P_e , according to (5).

The impact of fronthaul quantization on the error rate P_e is plotted in Fig. 3 as a function of the SNR for both fronthaul processing schemes under different fronthaul bit budgets. DtF is seen to outperform QF in the regime of high SNR, with crossing point occurring at lower SNR levels for a small fronthaul budget. This is because, with a sufficiently large SNR and small enough fronthaul capacity, the potential advantages of centralized detection at the CP are offset by the fronthaul quantization noise, and local detection is preferable.

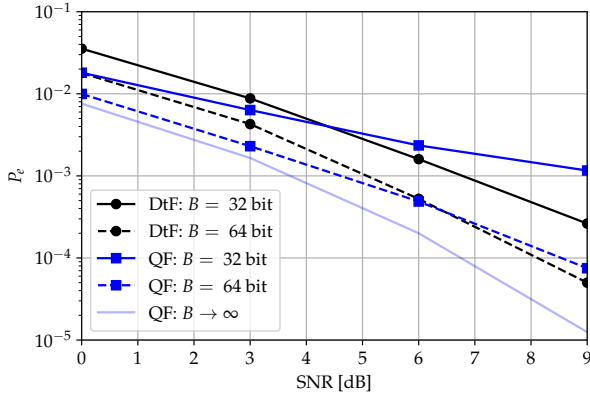


Fig. 3. Error rate versus SNR for F-RAN deployment with $L = 4$ ENs, signature length $N = 16$, and limited fronthaul capacity B .

The comparison depends also on the length N of the signature. To elaborate on this point, Fig. 4 plots the SNR required to meet a predefined reliability target $P_e \leq 10^{-3}$ as a function of the fronthaul bit budget B and the signature length N . As discussed, QF is preferable only at sufficiently large fronthaul capacity levels, and the required fronthaul capacity increases with the signature length N . In fact, for QF, in the presence of stringent fronthaul constraints, it is beneficial to trade signature length for quantization precision.

Finally, in Fig. 5 we analyze the trade-off between false positive rate, $P_{FP} \triangleq \frac{1}{M} \sum_{m=1}^M \Pr\{\hat{\xi}_m \neq 0 | \xi_m = 0\}$, and false negative rate, $P_{FN} \triangleq \frac{1}{M} \sum_{m=1}^M \Pr\{\hat{\xi}_m = 0 | \xi_m \neq 0\}$, obtained by varying the decision threshold. In line with the discussion so far, QF is seen to provide significant advantages when the fronthaul capacity B is sufficiently large. In contrast, the fronthaul requirement of DtF are more modest, but the performance of DtF is constrained by the limitations of local detection.

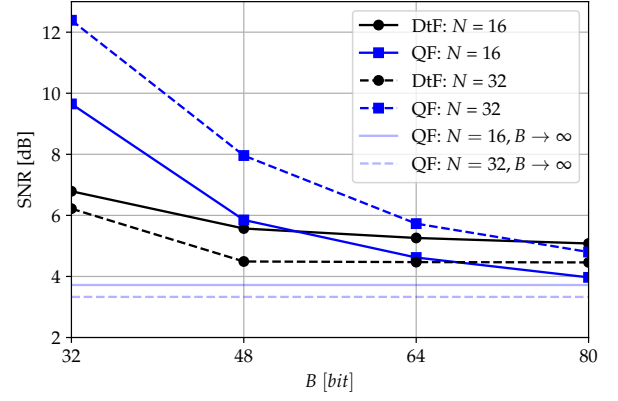


Fig. 4. Required SNR to achieve a target reliability $P_e \leq 10^{-3}$ as a function of the fronthaul link budget B and signature length N .

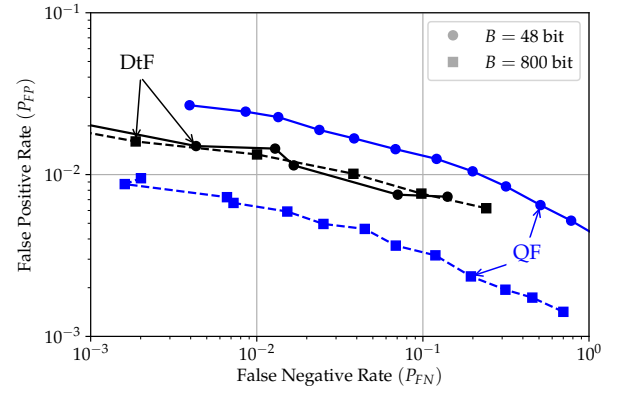


Fig. 5. Trade-off between false positive and false negative rates for different decision thresholds for $N = 32$ and $\text{SNR} = 0$ dB.

V. CONCLUSIONS

This paper has introduced a semantics-aware protocol for event-driven grant-free access in IoT F-RANs with fronthaul capacity constraints. The protocol adopts a joint source-channel coding scheme, based on a non-orthogonal generalization of TBMA, that directly detects the quantities of interest and yields spectral requirements that scale with the number of events to be monitored rather than with the number of devices. The power and spectral requirements are further improved through integration with cloud- and edge detection based on Bayesian message passing. We have evaluated numerically the relative performances of edge-cloud processing based on DtF and QF, and assessed the trade-offs between the codeword length, the fronthaul capacity and the required SNR, given a predefined reliability target. A general observation is that DtF outperforms QF in the presence of stringent fronthaul constraints, with the effect being more pronounced for higher SNR values. In this operational regime, the potential advantages of centralized detection at the CP are offset by the fronthaul quantization noise, and local detection is preferable. Further, in line with [14] we conclude that the proposed scheme offers a significantly higher spectral efficiency as compared to conventional TBMA by exploiting (i) sparse activation and (ii) structural dependencies between the variables for $L > 1$.

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